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**How places influence crime: The impact of surrounding areas on  
neighbourhood burglary rates in a British City, *Urban Studies***

**ABSTRACT**

Burglary prevalence within neighbourhoods is well understood but the risk from bordering areas is under-theorised and under-researched. If it were possible to fix a neighbourhood's location but substitute its surrounding areas, one might expect to see some influence on its crime rate. But by treating surrounding areas as independent observations, ecological studies assume that identical neighbourhoods with markedly different surroundings are equivalent. If not, knowing the impact of different peripheries would have significance for crime prevention, land use planning and other policy domains. This paper tests whether knowledge of the demographic makeup of surrounding areas can improve on the prediction of a neighbourhood's burglary rate based solely on its internal socio-demographics. Results identify significant between-area effects with certain types of periphery exerting stronger influences than others. The advantages and drawbacks of the Spatial Error and Predictor Lag model used in the analysis are discussed and areas for further research defined.

## **1. INTRODUCTION**

The ecological tradition within criminology explains neighbourhood crime in terms of social, demographic and criminogenic risks found within neighbourhoods. The extent to which neighbourhood crime might be affected by the characteristics of nearby surrounding areas is rarely considered (Dietz, 2002; Elffers, 2003). Focusing solely on within-neighbourhood effects assumes no interaction takes place between neighbourhoods leading to a situation whereby 'neighbourhoods with identical characteristics but dissimilar neighbouring characteristics are considered equivalent' (Deitz, p541). This treats the high crime neighbourhood as a 'crime scene' where the conditions that make it vulnerable to crime are to be found.

If it were possible to hold constant the location of a neighbourhood within a city but change some or all of its surrounding areas, it hardly seems tenable that this would not have some effect on that neighbourhood's crime rate. Surprisingly, the question as to whether the spatial arrangement of neighbourhoods, with all their attendant risks, elevates or lowers neighbourhood crime rates is seldom asked. Paradoxically, this mindset coexists with an awareness that the underlying causes of crime are traceable to broader processes (e.g. economic recession, demographic and social trends) that do not emanate from neighbourhoods, per se, but nonetheless, have an influence there.

Crime patterns and offender movements across neighbourhoods are explored, however, in Environmental Criminology (Wortley and Mazerolle, 2008) where the

emphasis is less on the social correlates of crime and more on the distribution of crime opportunities (Felson, 2002). Thus, urban design and land use may be responsible for the presence of facilities that attract opportunistic offenders (crime generators) or provide sites that are deliberately sought out by them to engage in premeditated illegal activity (crime attractors) (Brantingham and Brantingham, 1995). Permeable streets may lead to larger numbers of passers-by in general, or offer abundant entry points and escape routes for offenders specifically (Newman, 1972). Collectively, these may determine the extent to which motivated offenders, suitable targets and the absence of capable guardians against crime coalesce both spatially and temporally (Cohen and Felson, 1979).

Focussing on crime opportunities is driven by micro-level analyses of vulnerability which, at the area level, focus on buildings, streets, specific sites rather than entire neighbourhoods as the unit of analysis (Weisburd et al, 2009). Brantingham and Brantingham (1993) have observed how ‘the aggregate distribution of crime seems to be substantially related to the socio-economic and demographic mosaic of cities as well as the location of major population attractors’ (Brantingham, and Brantingham, 1993, p3). This articulates, very well, the importance of both the ecological and environmental approaches to understanding neighbourhood crime but also raises questions about the elevation or reduction in victimisation risks that stem from the spatial arrangement of neighbourhoods that define the urban mosaic.

The aim of this paper is to assess how far the positioning of neighbourhoods within the social mosaic - what is next to what - impacts upon neighbourhood burglary rates. The choice of domestic burglary is particularly appropriate for testing bordering neighbourhood effects because it is anchored to residential properties that have fixed spatial locations.

## **2. NEIGHBOURHOODS AND BURGLARY**

Research documenting and attempting to explain the distribution of residential burglaries is abundant. Distinctive patterns emerge. Burglaries can concentrate in the same neighbourhoods and along the same streets (spatial clustering, Johnson, 2010), afflict the same households (repeat victimisation, Farrell and Pease, 1993), happen at certain times of the day (Ratcliffe, 2002), feature specific modus operandi and occur more in some types of dwelling than in others (Townsend et al, 2003).

The identification of these patterns reflects a diversity of research approaches that may or may not include specific reference to residential areas even though their findings are clearly relevant to understanding crime risks within neighbourhoods. Neighbourhoods can serve as the context within which burglary occurs but can also be part of the explanation. The balance between these two roles varies with the theoretical and methodological perspective.

The notion of 'neighbourhood' is far more deeply embedded in ecological than analyses of burglary than in Environmental Criminology. Ecological perspectives are generally more focussed, albeit not exclusively, on socio-demographic influences on crime. Risk factors include concentrated poverty (Wilson, 1987), deficits of social cohesion and collective efficacy (Sampson et al, 1997) and spatial concentrations of both victims and offenders (Bottoms, 2006).

Shaw and McKay, 1942 argued that low socio-economic status, ethnic heterogeneity and population instability undermined community cohesion and informal social control, particularly of young people thereby, leading to higher crime (Shaw and McKay, 1942). Bursik spoke of the deleterious effects of 'social disorganisation' that he defined as 'the inability of local communities to realise the common goals of their residents or solve commonly experienced problems' (Bursik, 1988). Socially heterogeneous neighbourhoods, characterised by rapid population turnover and family disruption were at greater risk of social disorganisation. Temporary residents were less likely to facilitate social control, while heterogeneity acted as a barrier to communication, reducing the ability of residents to act collectively (Bursik 1988, Sampson and Groves 1989). Collective efficacy, the capacity for collective action between trusting neighbours, has been identified as a strong mediating factor on crime rates even in the face of adverse structural conditions such as high unemployment and concentrated poverty (Sampson et al, 1997).

In a recent analysis that linked data from the British Crime Survey with separate measures of neighbourhood disorder and socio-demographics, neighbourhoods were found to exert independent influences on individuals' fear of crime, not only, through visible signs of disorder and recorded crime, but also, through their social structure (Brunton-Smith and Sturgis, 2011).

Hipp (2011) studied 352 cities over a 30 year time span and revealed that the impact of inequalities in income on crime at neighbourhood level was stronger in cities with greater economic inequality, economic segregation and ethnic heterogeneity. He argued that the high level of inequality in such cities makes economic differences particularly salient to residents, which may lead to a perception of 'walled off neighbourhoods with strikingly different economic resources' (Hipp, 2011, p655).

The predominant concern in these ecological studies has been with how internal neighbourhood characteristics and socio-demographics influence neighbourhood crime outcomes using the neighbourhood as the unit of analysis and individuals, households or properties therein. Very few ecological studies have examined between-area effects. What little has been done has focused predominantly on fear of crime rather than burglary risk.

Covington and Taylor (1991) found that in Baltimore, fear of victimisation was affected, not only, by cultural differences between neighbours within

neighbourhoods but also, by differences between neighbourhoods. Focusing upon 'indirect victimisation' (where non-victimised individuals are affected by hearing about the victimisation of others), they found that differences in the socio-economic status and ethnicity of residents in the surrounding neighbourhoods elevated fear of crime.

A study in Merseyside provided some early evidence that neighbourhood crime levels might be influenced by the population and land use of surrounding neighbourhoods (Hirschfield and Bowers 1997, Bowers and Hirschfield, 1999). An analysis of 45 locations, where affluent areas directly bordered deprived neighbourhoods, found that the former tended to have higher levels of burglary and assault than affluent areas on Merseyside generally (Bowers and Hirschfield, 1999). Affluent areas bordering equally affluent areas had significantly lower crime rates than similar affluent areas surrounded by lower socio economic status neighbourhoods. In this particular bordering pattern, affluent areas operated as a protective 'buffer zone' offering immunity from victimization to neighbourhoods that already had relatively low crime risks.

With few exceptions, notably highly segregated residential areas and gated communities, the permeability of boundaries between neighbourhoods, for residents as well as offenders, means there is inevitably going to be some degree of interaction between them. People may move between neighbourhoods to visit family and friends, to access services, or as part of the journey to work or in pursuit

of selecting a burglary target. Neighbourhoods are not treated in isolation from their surroundings and nor should they be (Lupton, 2003).

### **3. RESEARCH QUESTIONS**

The assessment of between neighbourhood effects on burglary raises a number of questions.

The first is to ask how can the juxtaposition of different types of neighbourhood be represented?

Exploring this necessitates thinking about how to represent the neighbourhood in terms of size and location and importantly, the socio-demographic characteristics that distinguish it as a place. As the focus is on between-area effects, identifying where the neighbourhood fits within the social mosaic is essential. This requires identifying which other neighbourhoods share a border with it and what they are like as places. Fulfilling these tasks provides a foundation for the main research question, namely:

Does knowledge of the socio-demographic make-up of an area's surroundings improve on the prediction its burglary rate based solely on its internal socio-demographic composition?

Nested within this are two further questions, namely:



To what extent do different types of surrounding area contribute to an area's burglary rate ?

Which combination of surroundings has the greatest impact on an area's burglary rate?

Answering these questions extends the analysis by exploring the differential impacts, on burglary rates, of different types of periphery surrounding individual neighbourhoods. This potentially would enable, not only an identification of the implications for a neighbourhood's burglary rate that stem from where it is positioned within the social mosaic, but also, the consequences, for neighbourhoods, if their peripheries were to change for any reason (e.g. as a result of gentrification or decline).

Finally, we assess the following questions, namely:

What are the likely mechanisms underpinning potential bordering effects?

and

What are their theoretical and policy implications ?

The identification of potential bordering influences of different types of residential neighbourhood begs the question as to how such effects arise and why certain types of periphery might have greater impacts than others. We discuss potential mechanisms, the implications for crime prevention and set out an agenda for further research.

#### **4. DATA AND METHODOLOGY**

The British City of Leeds, was chosen to model between-neighbourhood effects on burglary. Leeds is a large local authority with a diverse population and incorporates each of the different types of residential neighbourhood found in other major British cities. It can be considered as a microcosm of urban Britain. It also featured as a case study in a broader research project on the uses of geospatial data in crime analysis (Newton, et al, 2011) which provided the foundations for this analysis. In addition, excellent relationships had been built up, over a number of years, with West Yorkshire Police, Safer Leeds (the local Crime and Disorder Reduction Partnership) and Leeds City Council which facilitated ready access to disaggregated recorded crime data and expert knowledge of local crime patterns. The City also had a relatively large number of domestic burglaries which was beneficial to a research exercise seeking to examine relationships between neighbourhood juxtapositions and crime.

The police recorded crime data comprised all offences in Leeds reported by the West Yorkshire Police in the period 1<sup>st</sup> April 2000 – 31<sup>st</sup> March 2002. The number of domestic burglaries in this dataset is quite large (N=8,418). Since 80% of burglaries with loss are reported, recorded burglary presents a reasonable representation of the true level of burglary (Dodd et al, 2004). The spatial distribution of burglary rates in the city is shown in Figure 1.

In the current work, the focus is on the relationship between burglary and the demographic composition of surrounding neighbourhoods (peripheries). This necessitated demarcating neighbourhood boundaries and identifying their the socio-demographic composition. Population Census Output Areas (OAs) provide a consistent, a priori means, of aggregation and come ready equipped with digital boundaries and social data. Leeds contained 2,439 OAs with an average population of around 300 and these provided the spatial framework for producing aggregate burglary counts from the disaggregated data and were the source for denominators for the derivation of burglary rates. Their use also affords the possibility to replicate the Leeds analysis for other cities in Britain. This would not be the case for zones defined using ad hoc criteria (e.g. land use, people's perceptions).

OAs were also the zones used in the creation of a nationally available geo-demographic classification of small areas in Britain, the Output Area Classification (OAC, Vickers et al, 2005). The different neighbourhoods in Leeds featured in this paper are from the OAC. Geo-demographic classifications, such as OAC, compare small areas across a range of socio-demographic indicators and group them into a discrete number of 'neighbourhood types' that are broadly similar in terms of their household composition, housing tenure, socio-economic status and employment, age structure, ethnicity and population turnover. They have been used extensively in marketing, resource allocation and in social research including the analysis of health inequalities (Petersen et al, 2011) higher education participation rates (Singleton, 2010), and crime (Ashby and Longley, 2005). A significant benefit of

the OAC is that it is a public domain classification, with a clear temporal match to the Leeds burglary data.

The OAC presents a hierarchical classification of area types that, at its most detailed level, identifies 52 sub groups which nest into 21 groups which, in turn, can be aggregated into 7 super groups. Each level of the classification has a label to describe the type of neighbourhood that it represents. The super groups range from 'Countryside', (agricultural areas and the rural urban fringe), and 'Prospering Suburbs' (affluent, family-oriented zones); through 'Typical Traits' (mixed housing and demographics) and 'Blue Collar Communities' (essentially working class neighbourhoods with mature populations); to 'Constrained by Circumstances' (low affluence), 'City Living' (some of the most disadvantaged areas) and 'Multicultural' areas (ethnically diverse communities). Further text descriptions and profiles of the demographic and social characteristics of each super group can be found in Vickers et al (2005). The 7 super groups were chosen for this analysis because they discriminate well between different types of neighbourhood and unlike the more detailed tiers of OAC, provide a manageable number of area types with which to identify spatial neighbourhood juxtapositions.

To the extent that crime patterns vary between neighbourhood types, and that the OAC represents local variations in social and demographic patterns, then a natural starting point for the spatial analysis of the incidence of burglaries by small area is the Analysis of Variance (ANOVA) model. One of the most appealing features of ANOVA is that it can be computed easily within a statistical package such as

SPSS. The ANOVA structure will be used as a basic reference model in the analysis which follows and can be expressed mathematically as:

$$Y = \beta X + \varepsilon \quad (1)$$

where  $Y$  is a column vector of burglary rates (whose individual elements  $y_i$  represent the burglary rate for area  $i$ ;  $X$  is a matrix of  $N_i = 2,439$  zones and  $N_j = 7$  area types in which each element  $x_{ij}$  is one if area  $i$  is classified into SuperGroup  $j$ , and zero otherwise;  $\beta$  is a column vector of parameters with  $\beta_j$  being the crime rate associated with SuperGroup  $j$ ; and  $\varepsilon$  is a vector of independent, normally distributed errors for each area ( $\varepsilon_i$ ) with zero mean and variance.

We will see below that the ANOVA model is able to capture variations in burglary to some extent, but has at least three notable characteristics. The first is that the use of OAC is an imperfect representation of neighbourhoods and their demographic composition. Secondly, that the crime rate for an OA depends only on the social profile of that OA and not of any neighbouring areas. Thirdly, that the random error terms ( $\varepsilon$ ) for each OA are independent.

The first of these could be challenged on a number of grounds, for example that the areas are too small or too large; or that the SuperGroup classification is a rather simplistic representation of multi-dimensional socio-demographic characteristics. Although we comment further on some of the possibilities in the discussion, alternatives and extensions to OAC are outside the scope of the current paper. Objections to features two and three which suggest independence of the crime rates between neighbouring areas have been spelled out in some detail in Sections 1 and

2 of this paper. In the analysis which follows we will explore a variety of models which incorporate the effects of spatial contiguity in both the crime rates and the errors. Since all of these models extend the basic ANOVA model by incorporating spatial effects in some ways, these will be termed SPANOVA (SPatial ANOVA) models.

To explore the extent to which the surroundings of an area have an impact on its burglary rate, it is necessary to distinguish the location of the focal area and that of the surroundings. The former can be thought of as the 'core' whilst the latter would represent that area's 'periphery' or 'hinterland'. To incorporate these effects in the models we will define a contiguity matrix  $W$ . The number of zones bordering area  $i$  is given as  $d_i$  and the individual cells  $w_{ik}$  take the value  $1/d_i$  if zone  $k$  borders area  $i$ , and zero otherwise. GIS software (ArcGIS 9.3) was used to produce a contiguity matrix of the 2,439 OAs in Leeds.

Now we define a suite of spatial models for the estimation of small area burglary rates according to the independence or autocorrelation of both the crime rates and the error terms as shown in Table 1. The models include two approaches to incorporating crime rates in the hinterland of each core area, based on scanning actual crime rates (which is introduced in model 2), and the use of average values for each of seven hinterland area types (models 3 and 5). Autocorrelation between the error terms, so that the error in a core area depends on the errors in each of seven hinterland area types, is introduced in models 4 and 5. In the next section, we report on the results of a calibration process for all of the models in Table 1,

with a particular emphasis on the way in which the proximity of neighbourhood types in the periphery affects burglary rates in the core areas.

INSERT TABLE 1 HERE

## 5. RESULTS

Having outlined a set of 5 possible models, the next stage is to assess the relative merits of the different models. A difficulty with this model suite, however, is that the models are not conveniently ‘nested’ - that is where one model can be considered as a special case of another - and this problematises the use of standard statistical hypothesis tests such as likelihood ratio or t-tests. For this reason, at least for the task of model choice, use of the Akaike Information Criterion (AIC) (Akaike, 1973) is adopted, as advocated by Burnham and Anderson (2002). The AIC test assumes that none of the models are true but that some approximate reality more closely than others, so that when faced with a number of alternative models to select from, it is proposed that the one with the minimum AIC should be used.

The AIC is shown for the full model suite in Table 2, along with two related measures. The *relative* AIC (denoted  $\Delta\text{AIC}$ ) shows for each model the difference between its AIC and the lowest AIC for all listed models.

The *Relative Likelihoods* can be interpreted as the relative probability that each model minimises the information loss in approximating reality. From this table, the Spatial Error and Predictor Lag Model (Model 5) was the best performing model, and has a relative likelihood of one. This model incorporates the effects of the peripheral OA super groups and also allowed for auto-correlated error terms (i.e. possible bordering effects that are not accounted for by super groups alone - the unexplained variance). The analysis suggests that Model 5 is the best performer by quite a large margin, as the relative odds of the next candidate (Model 2) is only 0.04. Note that the relative odds are related exponentially to the difference in AICs - regardless of the scale of absolute AIC. This surprises some people as in many situations, including that in table 2 here, the difference seems small in relation to the absolute values. In some respects AICs are similar to log-likelihood ratios (in fact under some circumstances they are equivalent) and like those quantities, it is only the difference between ratios that counts, not the absolute magnitude of the quantities being subtracted.

INSERT TABLE 2 HERE

The standard ANOVA can be viewed as a test of the counterfactual, namely, what one would expect to see if there were no periphery effects. The significant improvement of the Spatial Error and Predictor Lag Model over a standard ANOVA suggests that there is sufficient evidence that the surrounding areas do have an impact on burglary in the core neighbourhoods. The out-performance of Model 5 - which includes spatial autocorrelation between the geodemographics of



the core area and its neighbours - over the standard ANOVA - is a clear indication that the inclusion of periphery effects is a closer approximation to reality than the counterfactual. However, sight should not be lost of the fact that the error terms in Model 5 are also autocorrelated, indicating that there is further variance that is unexplained by the juxtaposition of the SuperGroups. Socio-demographic juxtapositions matter, but there are also other processes and interactions that are not yet represented explicitly in the model.

Figure 1 compares the observed burglary rates to the model estimates and the differences between the two.

INSERT FIGURE 1 HERE

It illustrates that the model appears to capture the general patterns of variation in burglary rates, particularly between the inner city and suburban areas. However, there is no obvious spatial ordering in the distribution of the residuals. This suggests that there was no systematic pattern in the location of OAs whose burglary rates were substantially higher or lower than those predicted by the juxtaposition of neighbourhoods. Areas where the model was a less effective predictor were scattered throughout the city. If the residuals had displayed a clear spatial pattern this would point to the presence of spatially ordered processes other than neighbourhood juxtapositions (e.g. street networks, land uses) exerting an influence on burglary. The absence of such patterns suggests that once the spatial effects as specified in the model are accounted for, all that remain in terms of error

are spatially uncorrelated random fluctuations - and therefore the model has adequately accounted for spatial patterns in the data.

INSERT TABLE 3 ABOUT HERE

Table 3 gives parameter estimates for the preferred model. For each OA, the predicted rate of burglary depends on the composition of both the core area and its periphery. For example, if a 'Blue Collar Community' is entirely surrounded by 'Countryside' then the expected burglary rate would be simply  $29.95 + 5.35 = 36.30$ . If a core area of 'Typical Traits' is bounded by 'City Living' and 'Multicultural' in equal measure then the expected rate would be  $24.42 + (0.5 * 56.14) + (0.5 * 41.78) = 73.38$ . The coefficients are presented in Table 3 as an ordered list, with the periphery value for Typical Traits set at zero to anchor the estimates. Thus the least desirable area to inhabit is shown as Multicultural, while the least attractive border would be City Living.

Nevertheless care must be exercised in this interpretation as the Standard Errors reported in Table 3 are fairly large. The 95% confidence interval around each estimate is approximately twice the standard error (S.E.), and as a rough significance test, any absolute value greater than twice the S.E. can be thought of as significantly different from zero. It may be reasonably safe to infer that Multicultural neighbourhoods provide the least desirable core areas, followed by City Living, but there is relatively little to choose between the remaining area types.

The parametrisation of area types in the periphery (Table 3b) affords strong and clear support for the idea that the characteristics of the hinterland have a profound influence on burglary rates in the core. In this case, not only is it undesirable to live in close proximity to City Living or Multicultural, but much more desirable to have any of Countryside, Prospering Suburbs or Typical Traits as adjacent types. In short, ‘who lives next to you’ looks just as important as ‘where you live’. This point can be reinforced if we return to an examination of actual burglary rates as shown in Table 4. These data show average rates for core area types (in the rows of the table) for instances in which there is a dominant area type in the periphery (shown in the columns of the table). Data are only shown in Table 4 for OAs in which more than 50% of the total number of areas that border them are of a single type. For example, if a core OA of type x is surrounded by 6 areas and at least 4 of these are of type y, then the burglary rate in this area is included in row x and column y of the table. Otherwise, the OA would not be included in this analysis.

Table 4 shows the average burglary rate and in parenthesis the number of OAs across this average is observed. For example, in 'Blue Collar' areas in which the dominant periphery is prospering suburbs then the average burglary rate is 16 crimes per thousand households, and there are 14 OAs of this type. Cells in which there are less than ten observations are shown in grey as potentially unreliable. Some of the trends which have been detected in Model 5 and discussed above can also be seen quite clearly in these data. For example, if we look at OAs with ‘Typical Traits’ then if these are adjacent to ‘Prosperous Suburbs’ then the rate is just 22, but this jumps all the way to 57 when the neighbours are ‘City Living’. In

areas which are 'Constrained by Circumstances' then we can see more than threefold variation between hinterlands which are 'Typical' and those which are 'Multicultural'.

INSERT TABLE 4 HERE

## **6. DISCUSSION**

The spatial model demonstrates that the demographic makeup of surrounding areas can improve on the prediction of a neighbourhood's burglary rate based solely on its internal socio-demographics. It does not, however, shed any light on the mechanisms by which these effects arise, for example, whether a certain type of bordering OA actually stops burglaries by deterring individuals in some way, or just increases crime risk by a lower amount than an alternative periphery. This ultimately requires undertaking qualitative research on whether the juxtaposition of different types of neighbourhood impacts upon offenders' choice of burglary targets and if so, how.

The model does provide a new perspective on burglary risk by treating the autocorrelation of spatially aggregated crime data, not as a statistical error to be corrected, but as part of the explanation as to why socio-demographically similar neighbourhoods may have elevated or lower burglary rates because of what surrounds them. The proposition that a neighbourhood's crime risk is never influenced by its surroundings is clearly untenable.

Peripheral effects need to be conceptualised in terms of 'contributing' to burglary rates observed in the core rather than 'raising' them. If this is done, one can think in terms of how much lower crime would be if a neighbourhood's surroundings had 'favourable' rather than 'unfavourable' geo-demographics in terms of crime risk. For example, the model indicates that, for Leeds, a Multicultural core entirely surrounded by City Living would have an estimated burglary rate of 99.6 burglaries per thousand households. The core effect alone would contribute 43.5 per thousand households (44% of the total rate) and the presence of the hinterland would contribute the remaining 56.1 per thousand households (56% of the total rate). Given that, in nearly all cases, an element of the core's crime rate will be attributable to what surrounds it, that same Multicultural core surrounded entirely by Prospering Suburbs would have the crime rate of 48.0 (43.5 per thousand + 4.5 per thousand) rather than 99.6 per thousand.

To give a hypothetical example, according to this model, if it were feasible ethically, politically, and financially to redevelop the surroundings of that Multicultural core and replace, in its entirety, the existing City Living periphery with a Prospering Suburban periphery, that would reduce the core burglary rate by over half from by 51.8% from 99.6 to 48.0 per 1,000 households.

Despite considerable same type clustering, there were examples of 'fractured ecologies' where the social and spatial processes that shape the urban fabric (Byrne and Sampson, 1986) resulted in some neighbourhoods being located cheek by jowl with markedly different communities, for example, where large

social housing schemes have been built near to prosperous suburbs on the periphery of cities (Hope 1999). These are geodemographically dispersed neighbourhoods, out of place in their surroundings, some with elevated crime risks and others benefiting from lower crime depending on the composition of the periphery.

One can anticipate what mechanisms might be at play. The most likely are the effects that bordering areas have on offender decision making and choice of target. Burglary offenders often offend within their own neighbourhoods, former neighbourhood and other 'anchor points' such as friends' homes, leisure sites as well as drug market locations (Wiles and Costello, 2000). They may venture into proximate neighbourhoods to commit burglaries because of a greater concentration of crime opportunities, lower levels of guardianship, poor natural surveillance or a combination of all of these. When they offend outside their immediate neighbourhood, there may be a greater propensity to do so in areas that are socially similar to their own (Reynald et al, 2008) and provide a more comfortable and attractive environment, offering camouflage and protection against exposure. The current model assumes that periphery effects contribute a fixed increment to burglary rates when combined with core areas. This precludes being able to assess interactions between specific cores and peripheries. Moving to core-dependent periphery estimates might give a better indication of the relationship between different super groups.

There was a high degree of spatial clustering among OAs belonging to the highest burglary super groups (Multicultural and City Living, table 4) which suggests that the potential for offenders from these neighbourhood types to commit burglary in the same area type, was high (albeit not necessarily involving flows from immediately adjacent OAs). The model showed that combinations of cores and peripheries from these two super groups predicted the highest burglary rates. These effects have a number of interpretations. The juxtaposition of a different high crime core and peripheral super group results in a) greater offending just within the core by resident offenders; or b) interaction between the two involving offender journeys to crime from the periphery to the core; or c) is attributable to other processes not encapsulated by neither the super groups nor the model.

The first proposition implies no physical interaction involving the movement of offenders between the two but rather that being surrounded by a different super group acts as a barrier to offender movement resulting in the deflection of offences back into the core. The second proposition implies that the core is more of a direct 'victim' of the criminogenics of the periphery in that the presence of offenders in the hinterland raises burglary rates in the core. For this to happen offenders would need to commit offences in areas that are socially dissimilar from their home neighbourhood. The degree of dissimilarity, however, is likely to be lower between these two high crime neighbourhoods than other super group combinations as both are relatively disadvantaged communities with mixed populations and similar types of housing. The third proposition includes the possibility, inter alia, that heterogeneity within the super groups masks subtle, but

important, differences between OAs belonging to the same category. This warrants analysis at a finer level of OAC but would require a larger number of observations than included in this study to make it reliable (see, below).

There is also the possibility that the selected neighbourhoods could reflect offenders' alternative choice of targets when displaced from their first choice by a crime prevention intervention or police activity given that crime tends not to displace into neighbourhoods that are substantially different in their social, economic and demographic characteristics (Brantingham and Brantingham, 2003).

It is likely to be the case that the propensity to offend in proximate neighbourhoods is greater still where access to these areas is easier due to the greater permeability of the street network. What remains to be tested is how much of the elevated burglary rates, in certain neighbourhood configurations, is due to street accessibility and how much is attributable to the socio-demographic composition of the juxtaposed areas.

Routine Activity theory (Cohen and Felson, 1979) suggests that other factors may influence burglary rates - for example if offenders cross an OA into neighbouring OAs (whether socially similar or not) as part of their daily routine, this will add to their familiarity with the crossed output area and possibly increase the chances of them offending there also.



## **7. CONCLUSIONS AND FURTHER RESEARCH**

The research presented in this paper is the first attempt at examining the impact of neighbourhood spatial configurations on burglary levels and has demonstrated, not only, that there are significant between-area effects, but also, that specific types of neighbourhood on the periphery have the greatest impacts. However, there are a number of caveats that need to be stated.

An inevitable limitation of using OAs is that they are not necessarily 'true neighbourhoods' in terms of their socio-demographics, size or boundaries. Neighbourhoods are created by the interaction of people and place and are neither fixed bounded entities or experienced in the same way by every resident (Lupton, 2003). OAs may also be too small to capture bordering effects. Even if the core, the periphery or both were to be defined using larger spatial units, this would not offer immunity from the Modifiable Aerial Unit Problem; the tendency for relationships between variables to change with the size of the spatial units of analysis (Openshaw, 1984). The definition of OA contiguity, namely, that the boundary of one area just has to touch that of another, does not take into account the length of the shared boundary and runs the risk of defining peripherality too loosely and of including areas that have limited connections with each other.

However, OAs were designed to be largely socially homogenous spatial units of roughly equal population size giving them a socio-geographic identity as opposed to being a purely administrative zone. Moreover, it would have been far more difficult to get a sense of the different types of residential area and how they intermingle spatially from an analysis of individual variables.

OAC super groups also have their limitations. The 7 tier super group level of OAC may be too broad to encapsulate fully the factors that elevate or reduce crime risks both within neighbourhoods and between them. The very existence of the OAC's finer-grained nested classifications at the group and sub-group levels indicates that the super groups have some degree of heterogeneity. Although focusing upon super groups in the City of Leeds has been sufficient to demonstrate the existence of between area effects on burglary, there would be clear advantages in up-scaling the analysis to a national level. This would enable any systemic patterns in neighbourhood juxtapositions to be identified across a number of cities and would produce a sufficiently large number of observations to move to the more detailed 'group' level of OAC, thereby reducing any social heterogeneity between OAs belonging to the same super group. The number of observations was too small to make this viable in Leeds.

In some cases, according to the model, peripheries contribute more crime to a core area's burglary rate than the core area itself. An enhancement would be to use disaggregated data on both burglaries and the residential location of the offenders who committed them, to determine if this is reflected in offender journey to crime patterns. This would enable the implicit assumption, that core area burglary is committed overwhelmingly by offenders from the periphery, to be tested.

The impact of the surroundings, on an area's crime rate, may well differ temporally. Being bounded by, for example, a City Living OA may raise the risk of being burgled at night time but reduce it during the day. The juxtaposition of other

neighbourhood types may have more serious implications for burglary in daylight hours.

Other potentially relevant mechanisms, by which spatial configurations potentially influence offender targeting, would need to be explored qualitatively, for example, how far cores and peripheries, identified using geo-demographics and OAs, are recognisable on the ground physically and through the perceptions of residents, offenders and police officers. Methods might include visual audits at the border between contrasting neighbourhoods to reveal local conditions and to identify what can be seen at the point of their juxtaposition and from different vantage points. Interviews with local residents in areas with uniform and contrasting hinterlands to establish how they regard those in neighbouring areas and how far they interact with them. Also, surveys to investigate how neighbouring areas affect residents' perceptions of safety, experience of crime, adoption of home security measures and levels of neighbourhood satisfaction. Interviews with offenders could be held to explore their awareness of the juxtaposition of different neighbourhoods and whether or not these feature in their choice of burglary target. Finally, the existence of between-area effects on crime could be studied in societies with varying degrees of ethnic, socio-cultural and economic segregation to assess their role and significance in shaping urban crime patterns.

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Table 1 spatial models for the estimation of small area burglary rates

Model	Name	Description	Mathematical expression
0	Null	No variation in crime rates between areas	$Y = X'$
1	ANOVA	Crime rates vary by area type (OAC)	$Y = \beta X + \varepsilon$
2	Spatial Autoregressive Lag	Crime rate in the core is related to actual crime rates in each area in the periphery	$Y = \rho WY + \beta X + \varepsilon$
3	Spatial Predictor Lag	Crime rate in the core is related to the mix of neighbourhood types in the periphery	$Y = \beta^* WX + \beta X + \varepsilon$
4	Spatial Error Lag	The variation (error) in crime rates in the core is related to the variations between area types in the periphery	$Y = \beta X + \lambda W\eta + \varepsilon$
5	Spatial Error and Predictor Lag	The crime rate in the core is related to the mix of area types in the periphery and the variation in crime rates is related to the variation in crime rates in the periphery	$Y = \beta X + \beta^* WX + \lambda W\eta + \varepsilon$

Table 2: AIC Scores of candidate models

	AIC	$\Delta AIC$	RL
Model 5: Spatial Error and Predictor Lag	23756.1	0.0	1.00
Model 2: Spatial Autoregressive Lag	23762.7	6.6	0.04
Model 3: Spatial Predictor Lag	23821.1	65.0	0.00
Model 4: Spatial Error Lag	24475.2	719.1	0.00
Model 1: Basic ANOVA Model	24814.8	1058.7	0.00
$AIC = 2k - 2\log(L)$ Relative likelihood (RL) = $\exp(-\Delta AIC/2)$			
k = number of parameters and L = maximised likelihood of the model			

Table 3 Model Coefficient Estimates

<b>3a. Core Neighbourhood Type</b>	Estimate	S.E.
Multicultural	43.51	4.30
City Living	35.72	4.26
Blue Collar Communities	29.95	3.79
Constrained by Circumstances	29.56	3.86
Countryside	29.20	5.49
Prospering Suburbs	25.97	3.66
Typical Traits	24.42	4.06
<b>3b. Periphery Neighbourhood Type</b>	Estimate	S.E.
<b>Periphery:</b> City Living	56.14	6.79
<b>Periphery:</b> Multicultural	41.78	6.12
<b>Periphery:</b> Blue Collar Communities	20.81	6.02
<b>Periphery:</b> Constrained by Circumstances	15.32	5.35
<b>Periphery:</b> Countryside	5.35	9.68
<b>Periphery:</b> Prospering Suburbs	4.52	5.07
$\lambda$ (Spatial Error Autoregression)	0.67	0.02

Notes: S.E. = Standard Error

Table 4 Variation in burglary rates by area type

Area type (core)		Area type (periphery)						
		Blue Collar	City Living	Country-side	Prospering Suburbs	Constrain'd	Typical Traits	Multi Cultural
	Blue Collar Communities	<b>22</b> (41)	-	8 (1)	<b>16</b> (14)	<b>26</b> (57)	<b>16</b> (36)	61 (8)
	City Living	24 (2)	<b>73</b> (96)	-	<b>20</b> (16)	16 (3)	<b>20</b> (17)	<b>43</b> (17)
	Countryside	63 (1)	-	8 (7)	<b>13</b> (17)	-	11 (9)	-
	Prospering Suburbs	28 (7)	54 (5)	<b>24</b> (9)	<b>20</b> (224)	46 (4)	<b>27</b> (55)	44 (2)
	Constrained Circumstances	<b>24</b> (35)	41 (2)	-	16 (7)	<b>26</b> (158)	<b>14</b> (34)	<b>48</b> (11)
	Typical Traits	<b>19</b> (12)	<b>57</b> (11)	8 (6)	<b>22</b> (41)	<b>31</b> (23)	<b>21</b> (182)	32 (8)
	Multicultural	52 (2)	<b>50</b> (19)	-	23 (4)	<b>38</b> (12)	33 (7)	<b>37</b> (159)

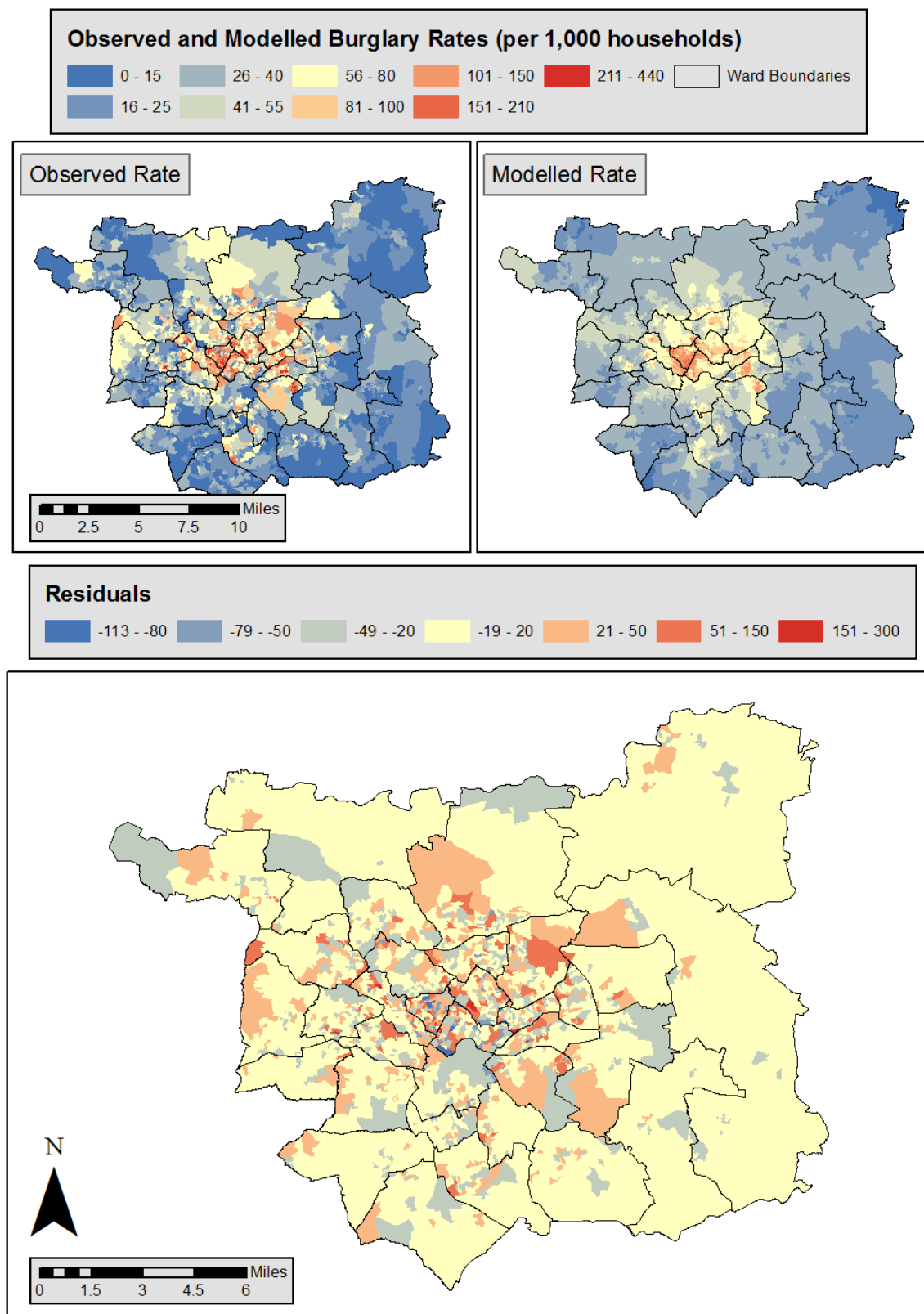


Figure 1 Observed and modelled burglary rates with residuals